# Rain rate quantiles retrieved from GMI brightness temperatures

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# Background

With the advent of GPM, we often deal with far more difficult and varied surfaces than was (usually) the case for TRMM:

- Variable snow cover
- Variable vegetation
- Variable sea ice
- Complex spatial mixtures of land, wetlands, open water

# Background

More surface complexity and variability combined with generally weaker, shallower precipitation implies

- Less signal
- More noise
- Low overall radiometric sensitivity to precipitation and potentially large retrieval errors

# Two distinct approaches to high-latitude retrievals

1. Try to *specify* or explicitly *retrieve* surface properties; OR
2. Design the algorithm to treat the background as *noise* and use channel combinations that *reduce sensitivity to that noise* while *retaining sensitivity to precip*.

# Two distinct approaches to high-latitude retrievals

1. Try to *specify* or explicitly *retrieve* surface properties; OR
2. Design the algorithm to treat the background as *noise* and use channel combinations that reduce sensitivity to that noise while retaining sensitivity to precip.

The second approach is sometimes referred to as the “surface-blind” or “S0” approach.

# The conceptual basis for S0 retrievals is not new!

- Weinmann and Guetter (1977) used an ad hoc linear combination of 19V and 19H channels to eliminate the strong contrast between land and ocean.
- Spencer et al. (1989) did essentially the same thing for SSM/I 85 GHz channels – *polarization corrected temperature* (PCT)
- Grody's "scattering index" (1990s) was a more elaborate (but still ad hoc) multifrequency method.

# UW-Madison algorithm

- *Formalizes*, *generalizes*, and *optimizes* the S0 approach using objectively derived linear transformations of GMI channels (10–89 GHz, dual polarization).
- Requires only *statistical* information about temporal and spatial background TB variability ("noise") in the form of channel means, covariances.
- Currently still a standalone algorithm, but methods could be seamlessly integrated into GPROF today.

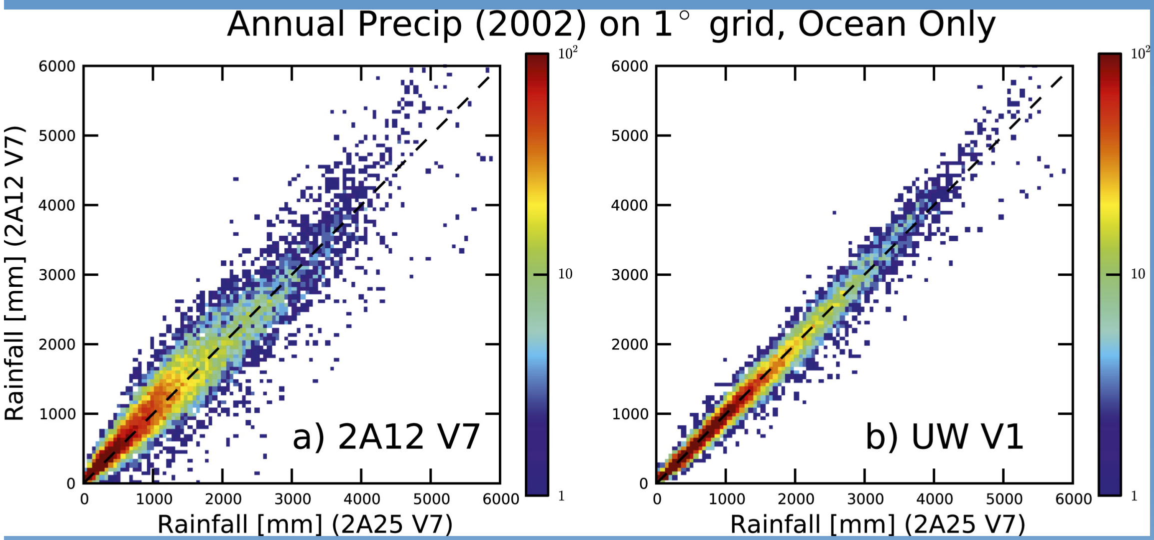
# UW-Madison Algorithm

- Bayesian
- Trained on over two year's worth of matchups with near-nadir DPR Ku-band rain rate
- Uses resolution-matched GMI Tbs
- Employs dimensionality reduction (9 channels to 3 pseudochannels + 2 env. variables) based on covariance of background TB variability in 12 static surface classes, further stratified by surface skin temperature ("warm" or "cold")
- Automatic fallback if too few samples found in 5D space
- Completely objective implementation, no subjective channel weightings or match criteria; no ad hoc IF statements; no "screens."
- In most cases, $10^2$–$10^6$ matches found for any given GMI scene
- Robust posterior CDFs (or quantiles) of rain rate

# Recap for TMI

- Published in Petty and Li (2013), Parts I and II, *J. Atmos. Ocean. Tech.*
- Validated globally for 2012 and 2015
- Compared with GPROF / 2A12 v. 7
- Complete 17-year TMI record has been processed and will be posted on a suitable server soon.

# TMI Validation




| Class | Ratio 2A12 (2002) | Ratio UW (2002) | Ratio UW (2005) | RMS error 2A12 (2002) | RMS error UW (2002) | RMS error UW (2005) | Correlation 2A12 (2002) | Correlation UW (2002) | Correlation UW (2005) |
|---|---|---|---|---|---|---|---|---|---|
| Ocean | 1.04 | 1.00 | 0.99 | 260 | 129 | 129 | 0.96 | 0.99 | 0.99 |
| 1w | 1.09 | 1.01 | 1.00 | 602 | 309 | 298 | 0.73 | 0.91 | 0.92 |
| 2w | 0.68 | 0.97 | 0.96 | 640 | 343 | 357 | 0.86 | 0.94 | 0.95 |
| 3w | 0.75 | 1.04 | 0.98 | 150 | 90 | 94 | 0.75 | 0.79 | 0.82 |
| 4w | 1.00 | 1.00 | 1.05 | 692 | 425 | 503 | 0.70 | 0.81 | 0.73 |
| 5w | 2.38 | 1.02 | 1.09 | 676 | 85 | 77 | −0.05 | 0.83 | 0.82 |
| 6w | 8.56 | 0.67 | 0.70 | 4221 | 406 | 400 | 0.62 | 0.26 | 0.23 |
| 1c | 3.06 | 1.11 | 1.00 | 1282 | 390 | 235 | 0.24 | 0.87 | 0.32 |
| 2c | 0.43 | 1.13 | 2.23 | 334 | 180 | 267 | 0.84 | 0.85 | 0.16 |
| 3c | 3.72 | 2.39 | 1.36 | 150 | 21 | 49 | 0.09 | 0.55 | 0.22 |
| 4c | 11.09 | 1.05 | 0.70 | 3087 | 99 | 190 | −0.63 | 0.99 | 0.33 |
| 5c | 5.85 | 0.81 | 0.99 | 540 | 41 | 37 | 0.27 | 0.33 | 0.22 |
| 6c | 3.02 | 0.52 | 0.52 | 1020 | 357 | 353 | 0.17 | 0.77 | 0.66 |

# Adaptation to GMI

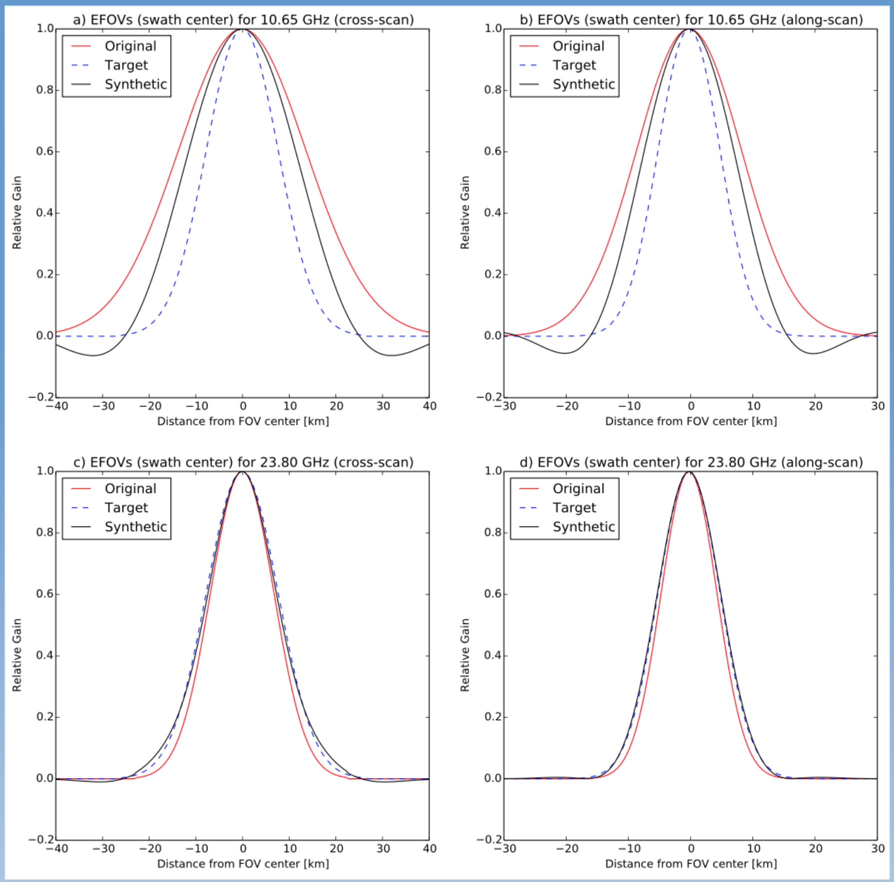
- Required resolution-matched channels
- Needed adequate GMI-DPR matchup dataset to objectively define land classes, derive channel transformations, and populate the *a priori* data base (5D lookup table for each surface class).
- Current version retrieves DPR near-surface rain rate.

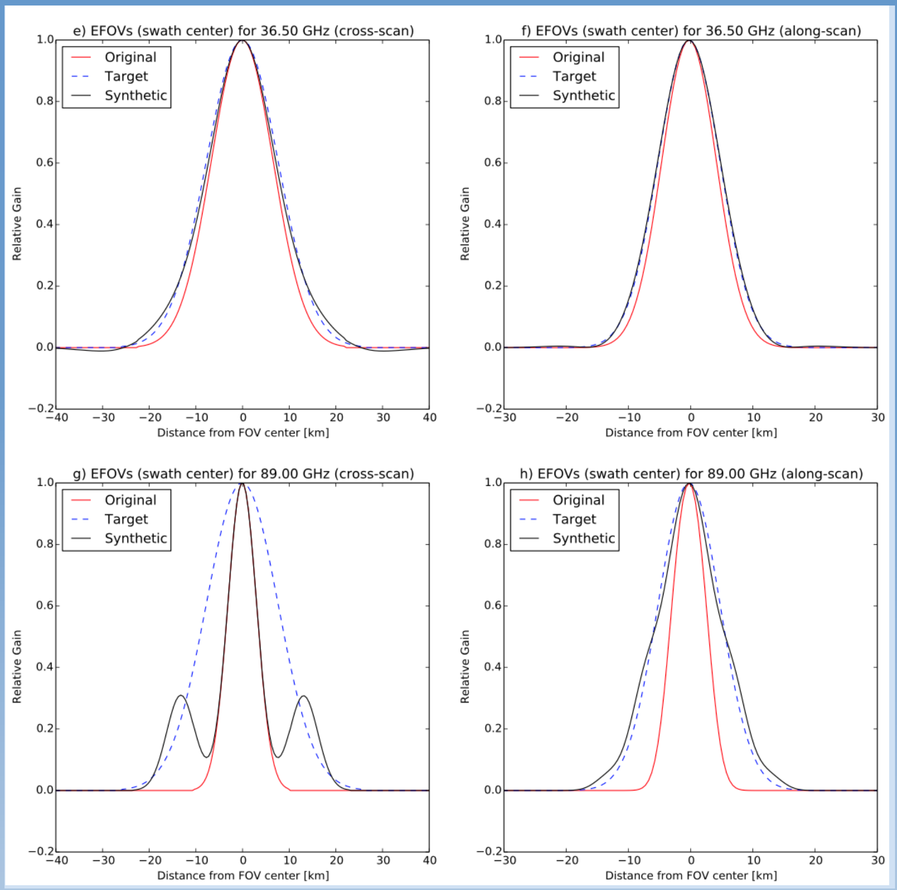
# GMI Field-of-View matching

Why do we care?

- Mismatched footprints introduce severe noise in the vicinity of sharp spatial gradients (e.g., coastlines)
- Worse: that noise is non-linearly correlated between channels so it *cannot* be completely removed via principal component transformations.

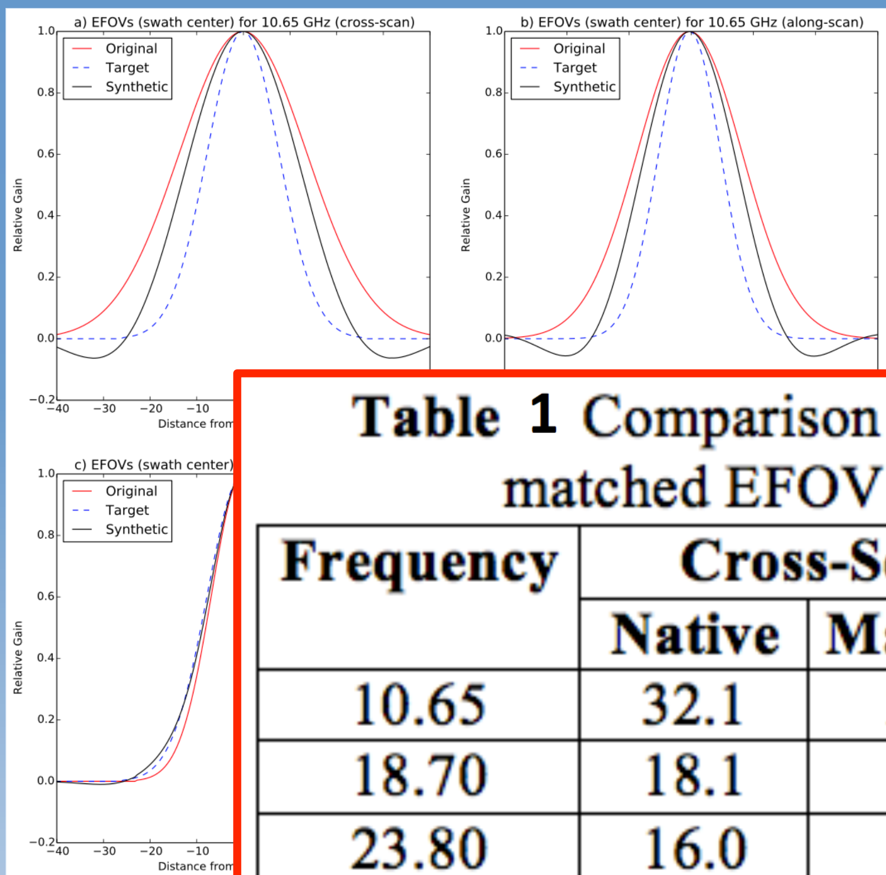
# GMI Field-of-View matching




Petty, G. W. and Bennartz, R. (2017): Field-of-view characteristics and resolution matching for the Global Precipitation Measurement (GPM) Microwave Imager (GMI), Atmos. Meas. Tech., 10, 745-758

# GMI Field-of-View matching



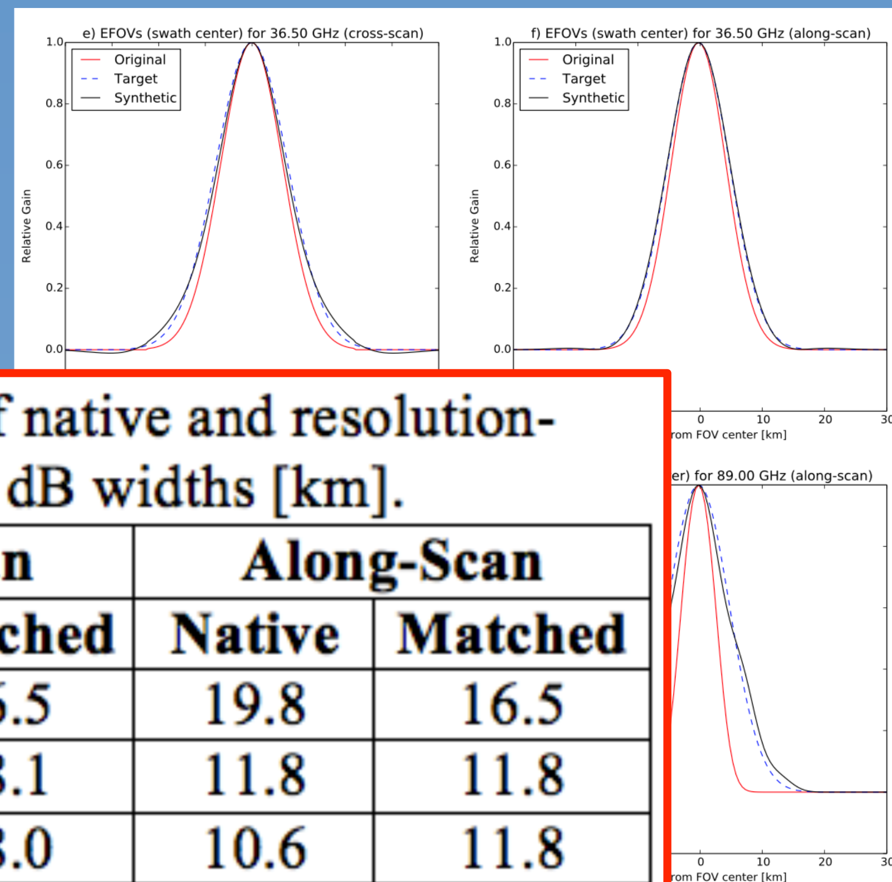
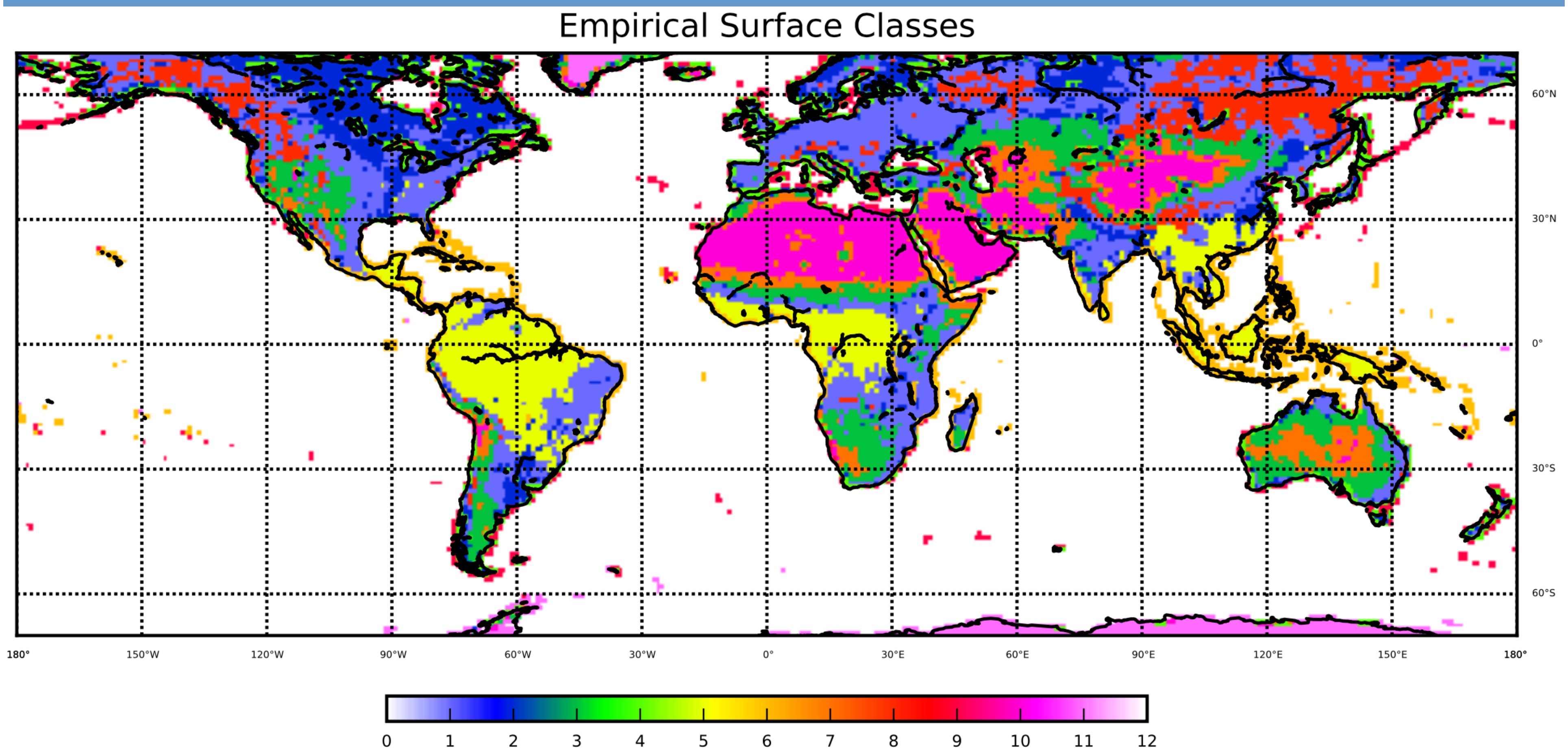




**Table 1** Comparison of native and resolution-matched EFOV 3 dB widths [km].

| Frequency | Cross-Scan | | Along-Scan | |
|---|---|---|---|---|
| | Native | Matched | Native | Matched |
| 10.65 | 32.1 | 26.5 | 19.8 | 16.5 |
| 18.70 | 18.1 | 18.1 | 11.8 | 11.8 |
| 23.80 | 16.0 | 18.0 | 10.6 | 11.8 |
| 36.50 | 15.6 | 18.0 | 10.3 | 11.8 |
| 89.00 | 7.2 | (7.2) | 6.3 | 11.8 |

# GMI land surface classes



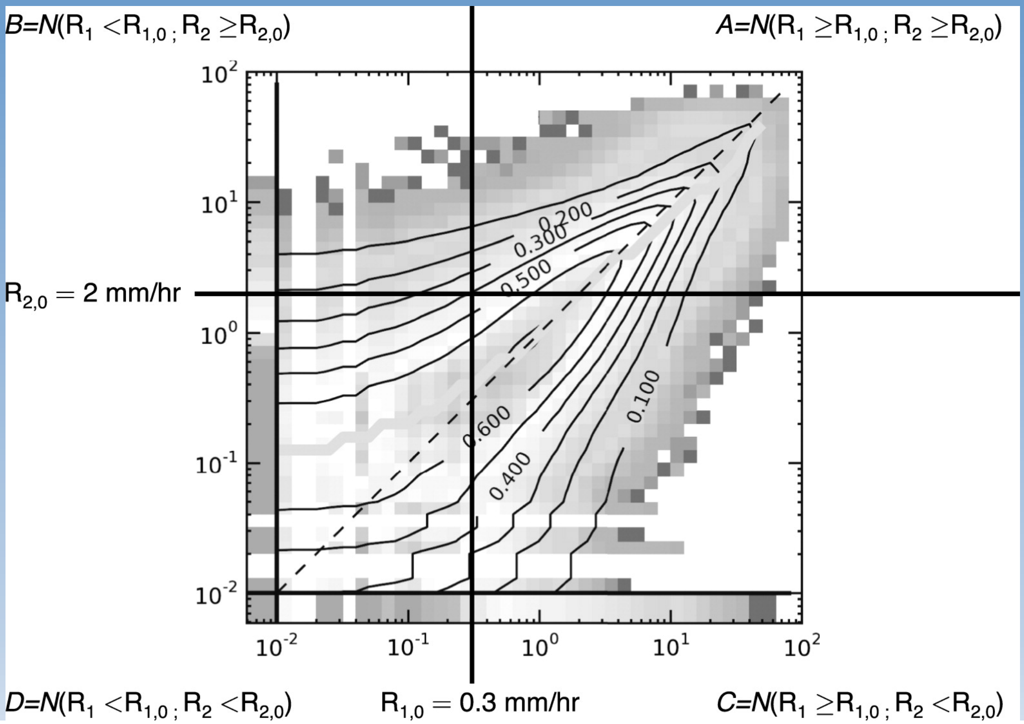

Based on novel unsupervised classification scheme applied to a pairwise “similarity” metric applied to annual multichannel brightness temperature means & covariances from precipitation-free scenes.

# Current status

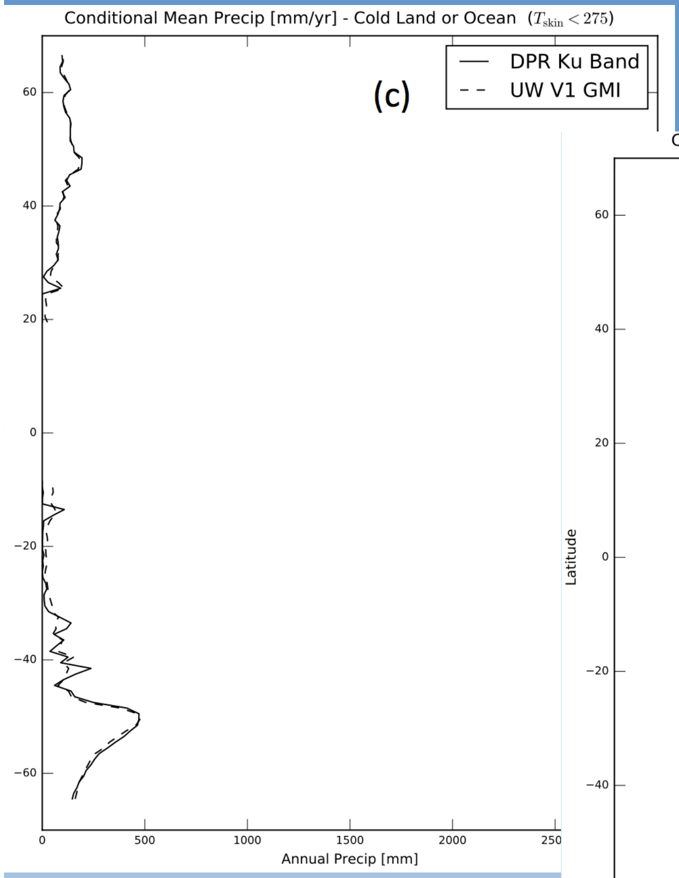
- Pre-distilled lookup table based on one-half of the available near-nadir DPR-GMI matchups since launch.
- Approximately 340 million matches
- Validation is underway using the other half of the matchups.

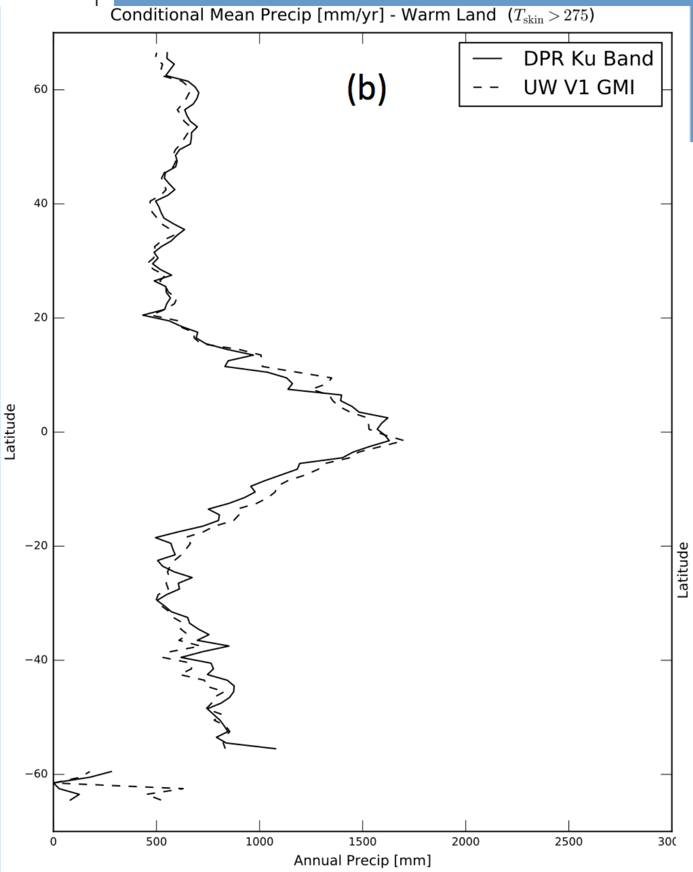
# Preliminary validation for GMI

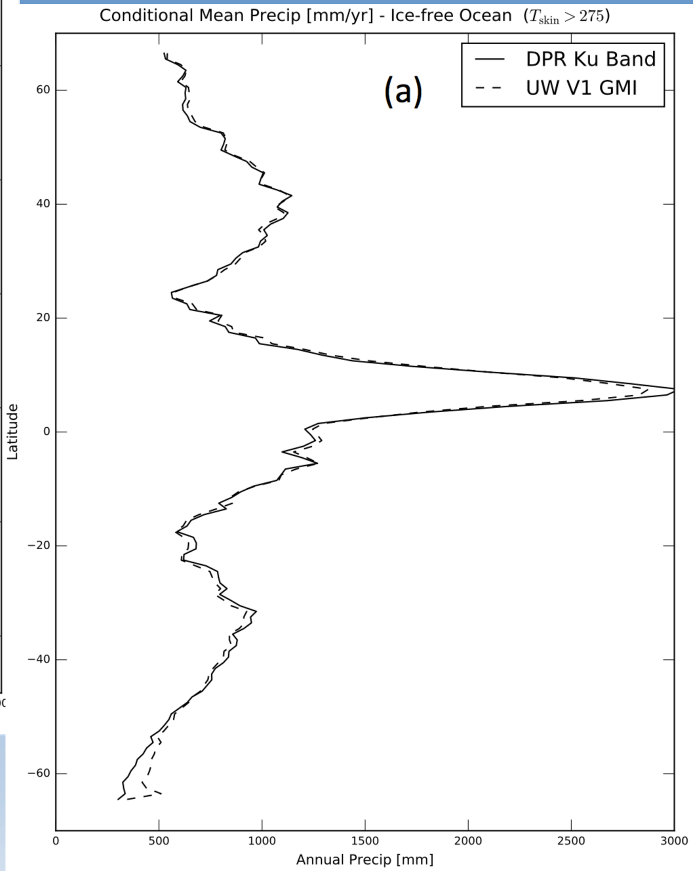
- Pixel by pixel skill for all land classes, warm and cold surfaces.
- Annual totals compared between GMI and DPR (near-nadir only) on 1 degree grid.
- No comparisons yet with GPROF.



# Latitudinal profiles – first year



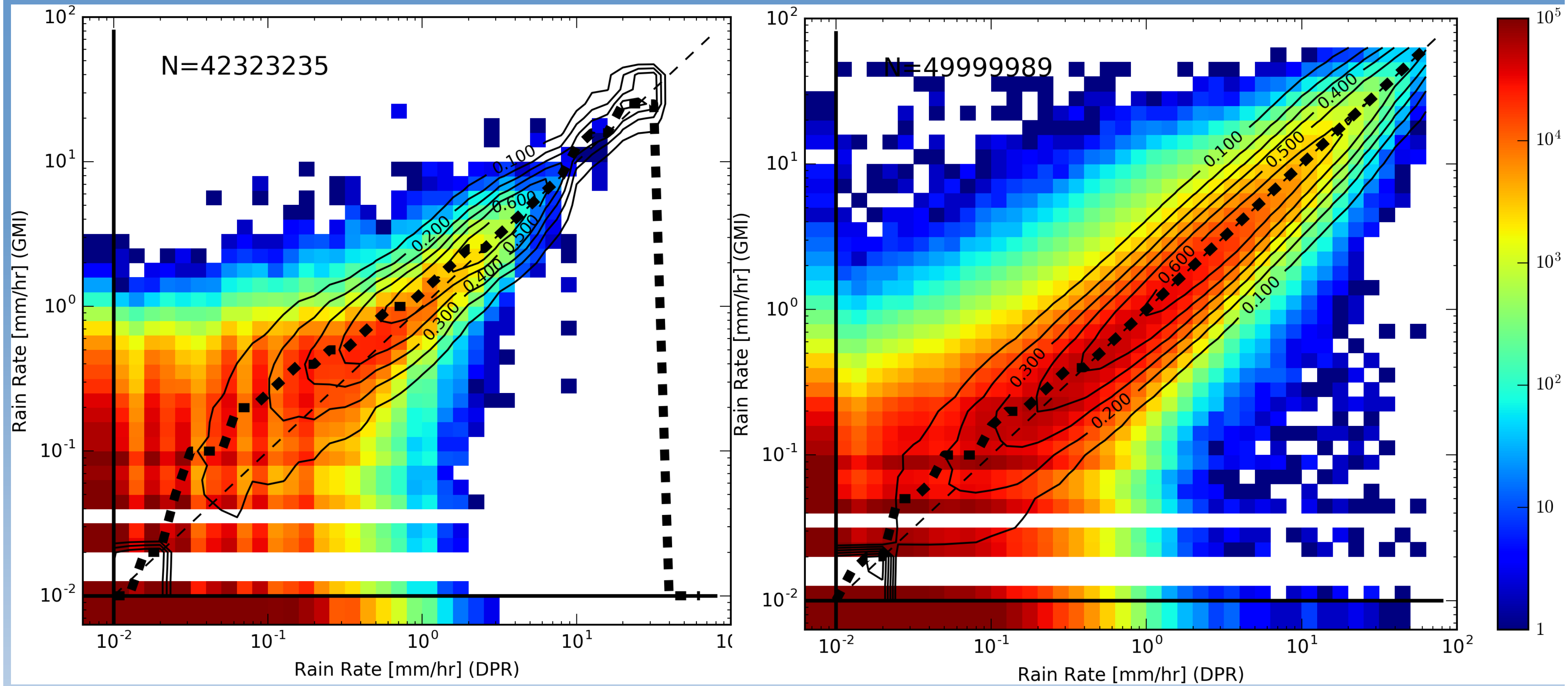



# Class 0 (ocean)

$T_{skin}$ < 275 K

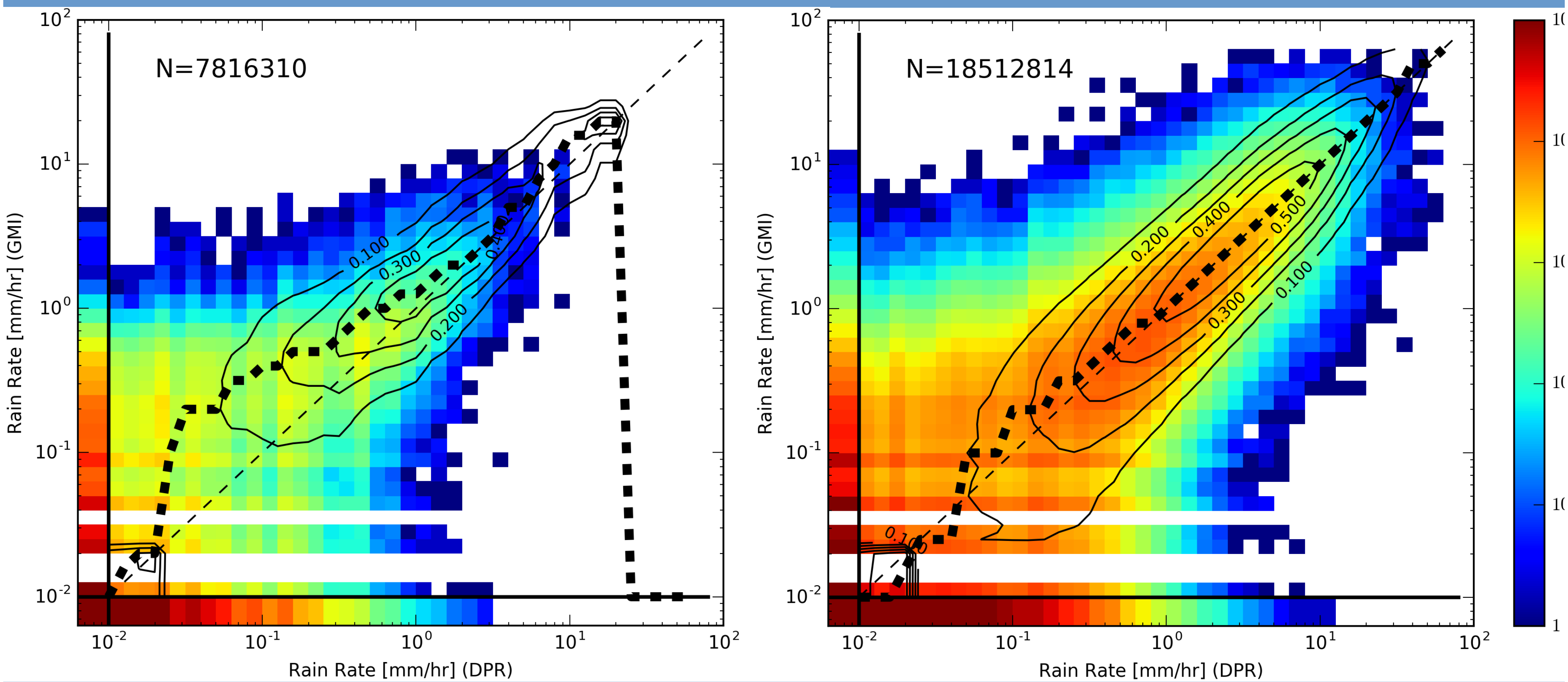
$T_{skin}$ > 275 K



# Class 1

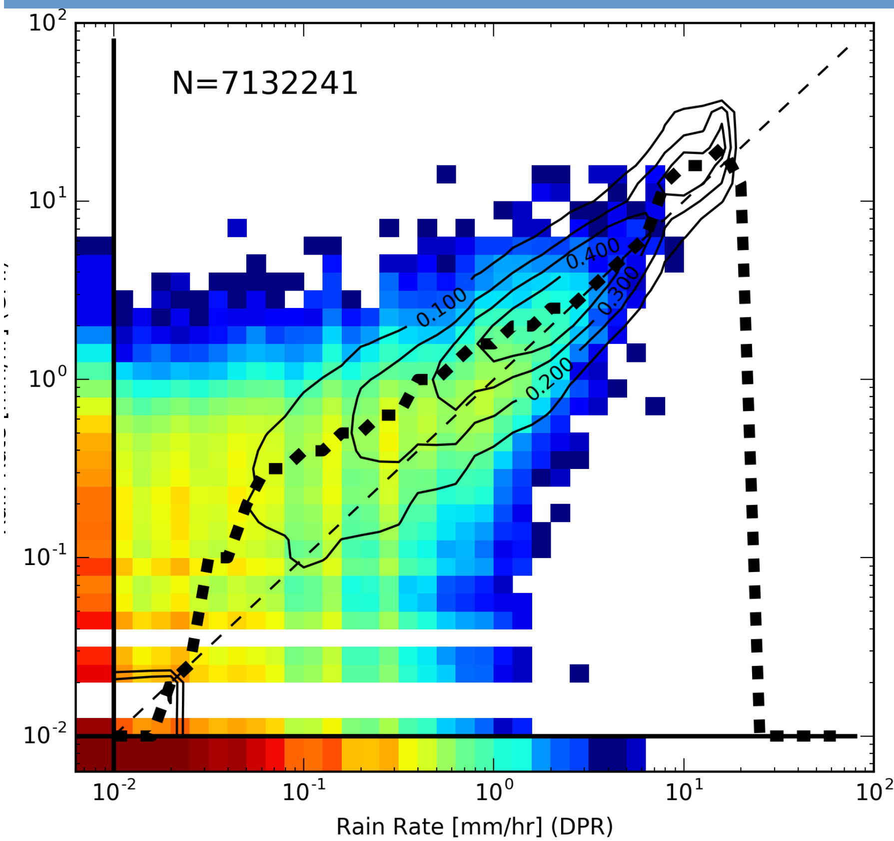
$T_{skin}$ < 275 K

$T_{skin}$ > 275 K

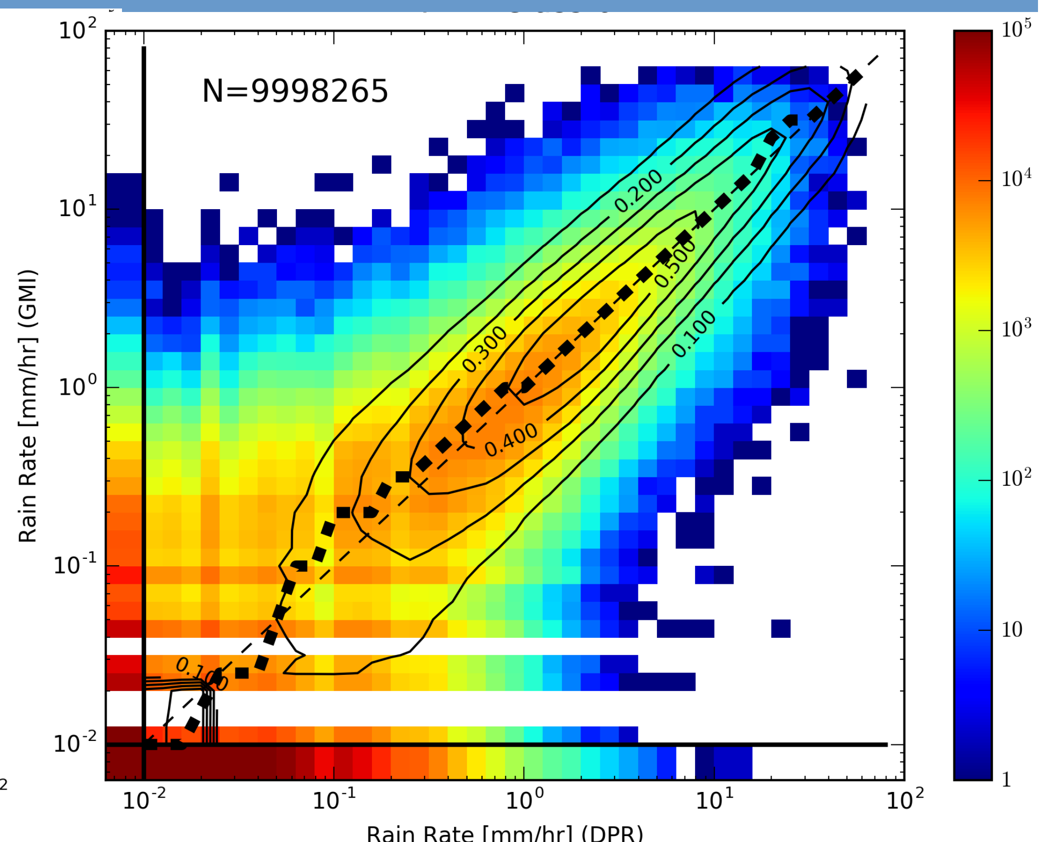


# Class 2

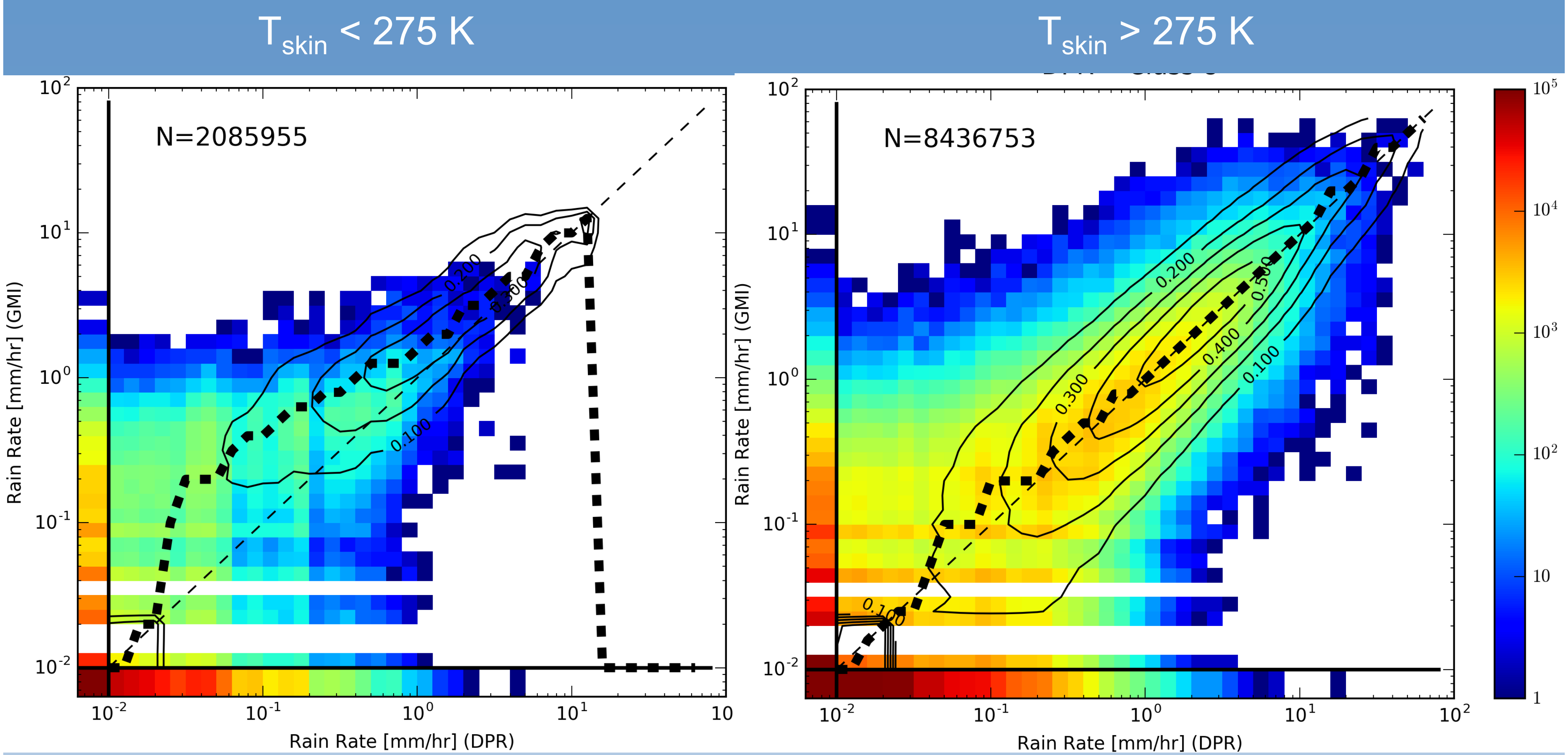
$T_{skin}$ < 275 K




$T_{skin}$ > 275 K



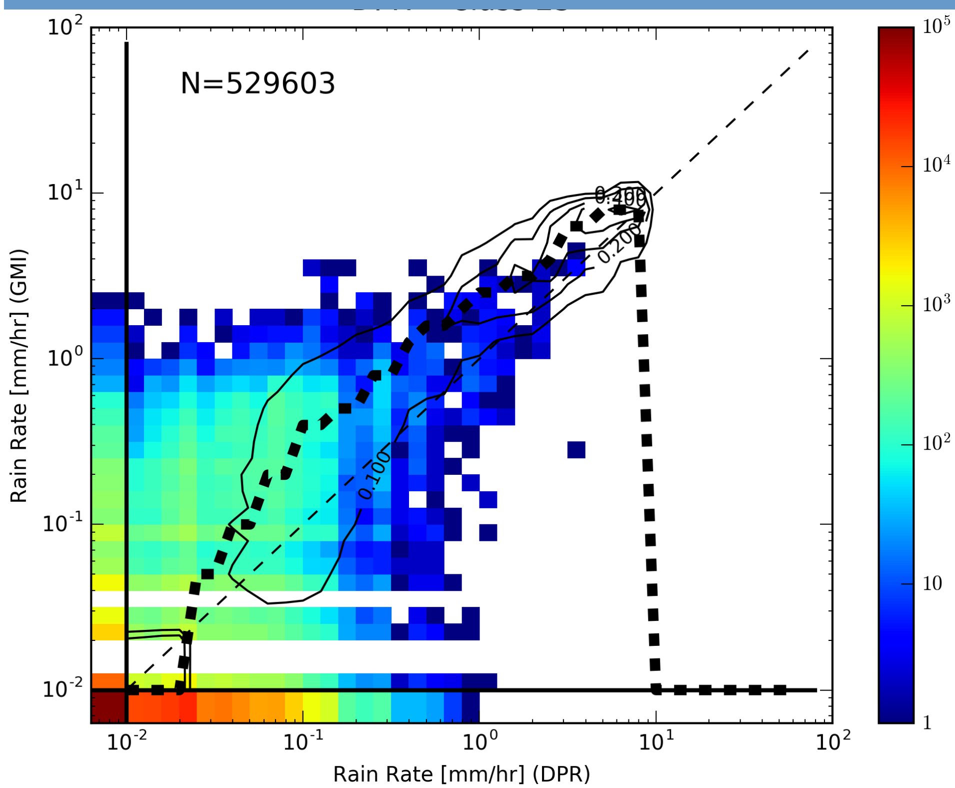
# Class 3



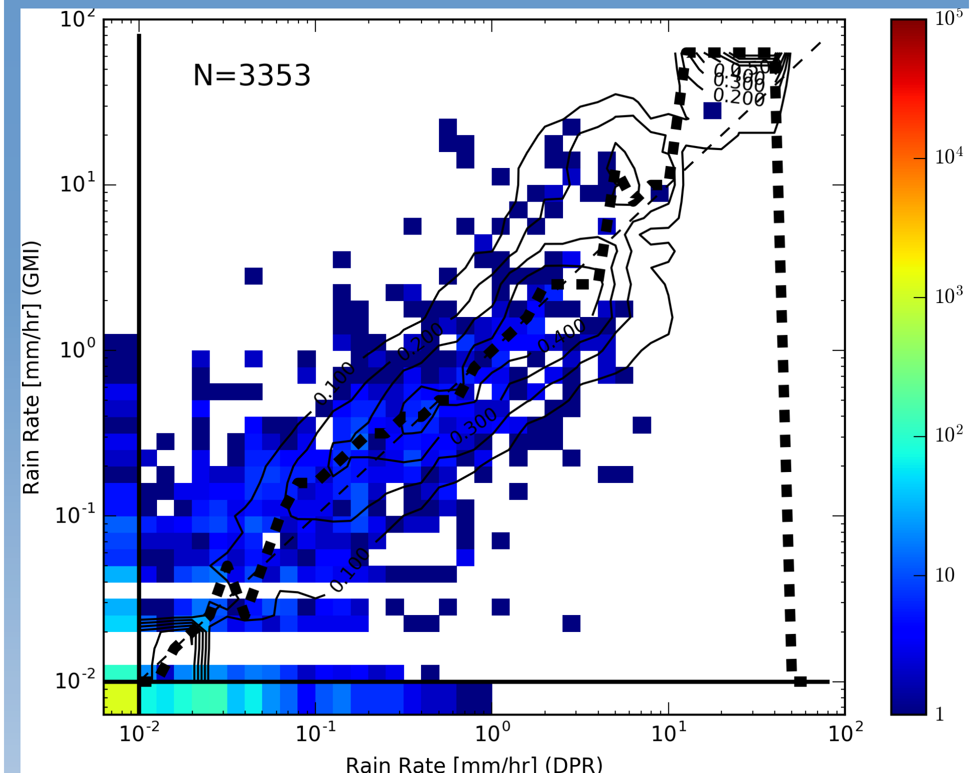
$T_{skin}$ < 275 K
$T_{skin}$ > 275 K
N=2085955
N=8436753
0.200
0.300
0.100
0.400
0.500
Rain Rate [mm/hr] (GMI)
Rain Rate [mm/hr] (DPR)
$10^{-2}$
$10^{-1}$
$10^{0}$
$10^{1}$
$10^{2}$
1
10
$10^{2}$
$10^{3}$
$10^{4}$
$10^{5}$

# Class 11

$T_{skin}$ < 275 K




$T_{skin}$ > 275 K



# So much for run-of-the-mill rain rate retrievals…

Let’s talk about *quantiles*, which is the *unique* feature of the UW-Madison algorithm

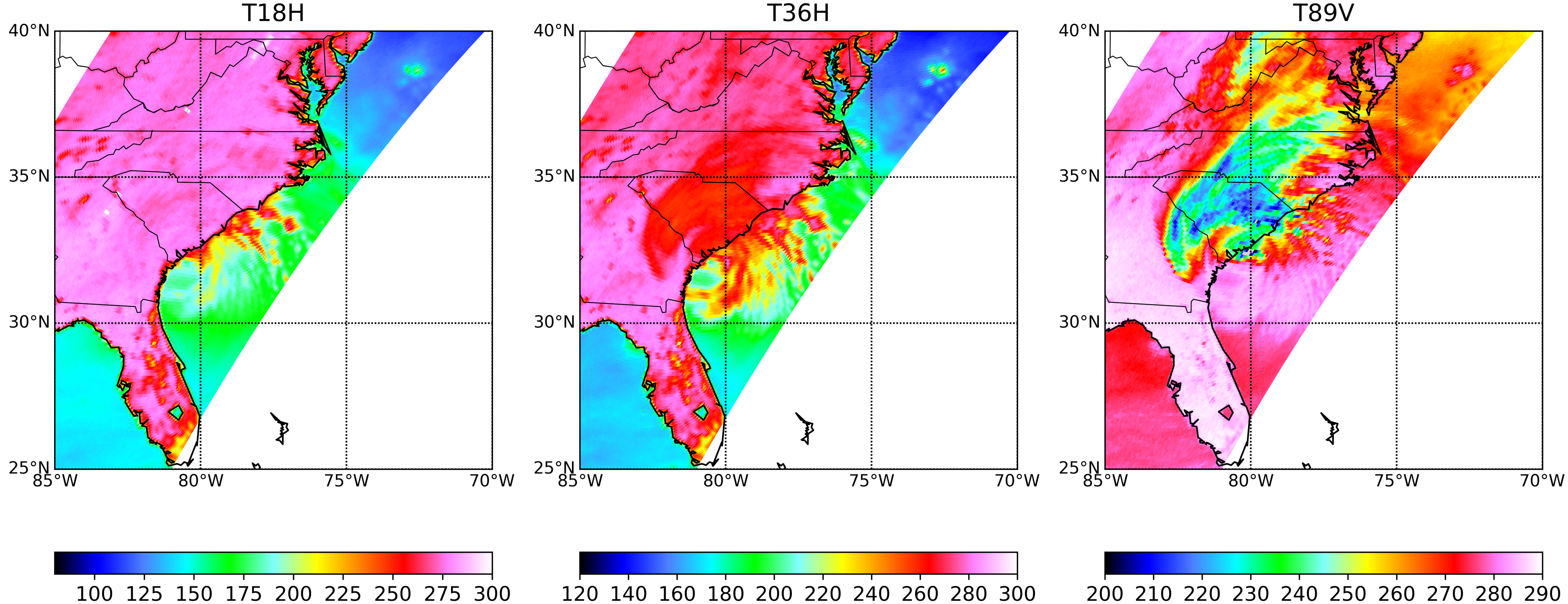
We’re able to retrieve quantiles only because the S0 methodology (and associated dimensional reduction) yields very large numbers of DPR matches for most scenes.

# What good are quantiles?

- Error bars! They answer the age-old question: What is the *range* of plausible rain rates associated with *this* pixel?
- Quantiles (or percentiles) tell you the fraction of DPR rain rates for a given scene below a particular value. For example:
  - 10%-ile: Ten percent of DPR matchups fall below this value.
  - 50%-ile (median): half of DPR matchups fall below this value; the other half above
  - 90%-ile: Ten percent of DPR matchups fall above this value

# Hurricane Matthew

October 8, 2016



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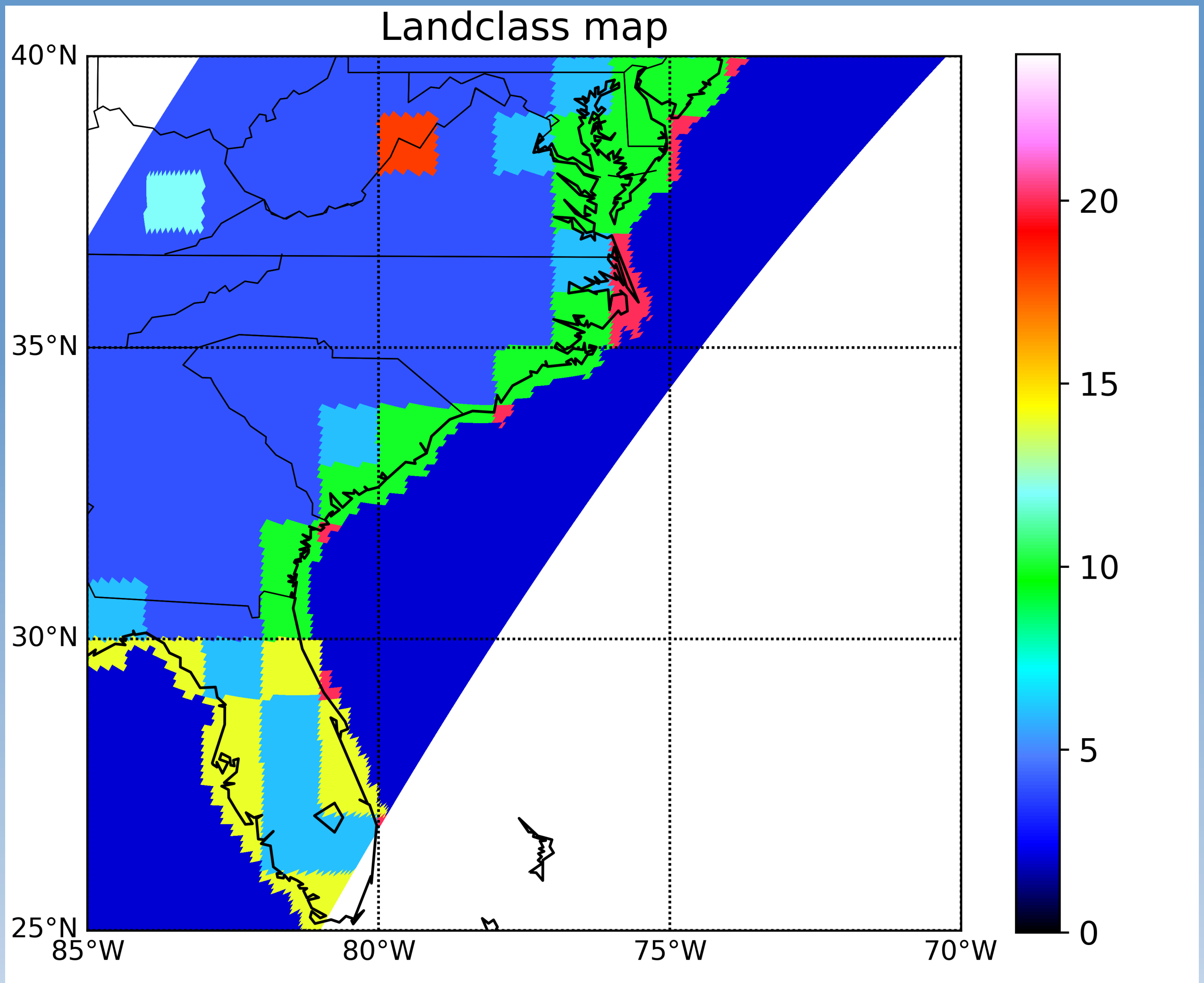

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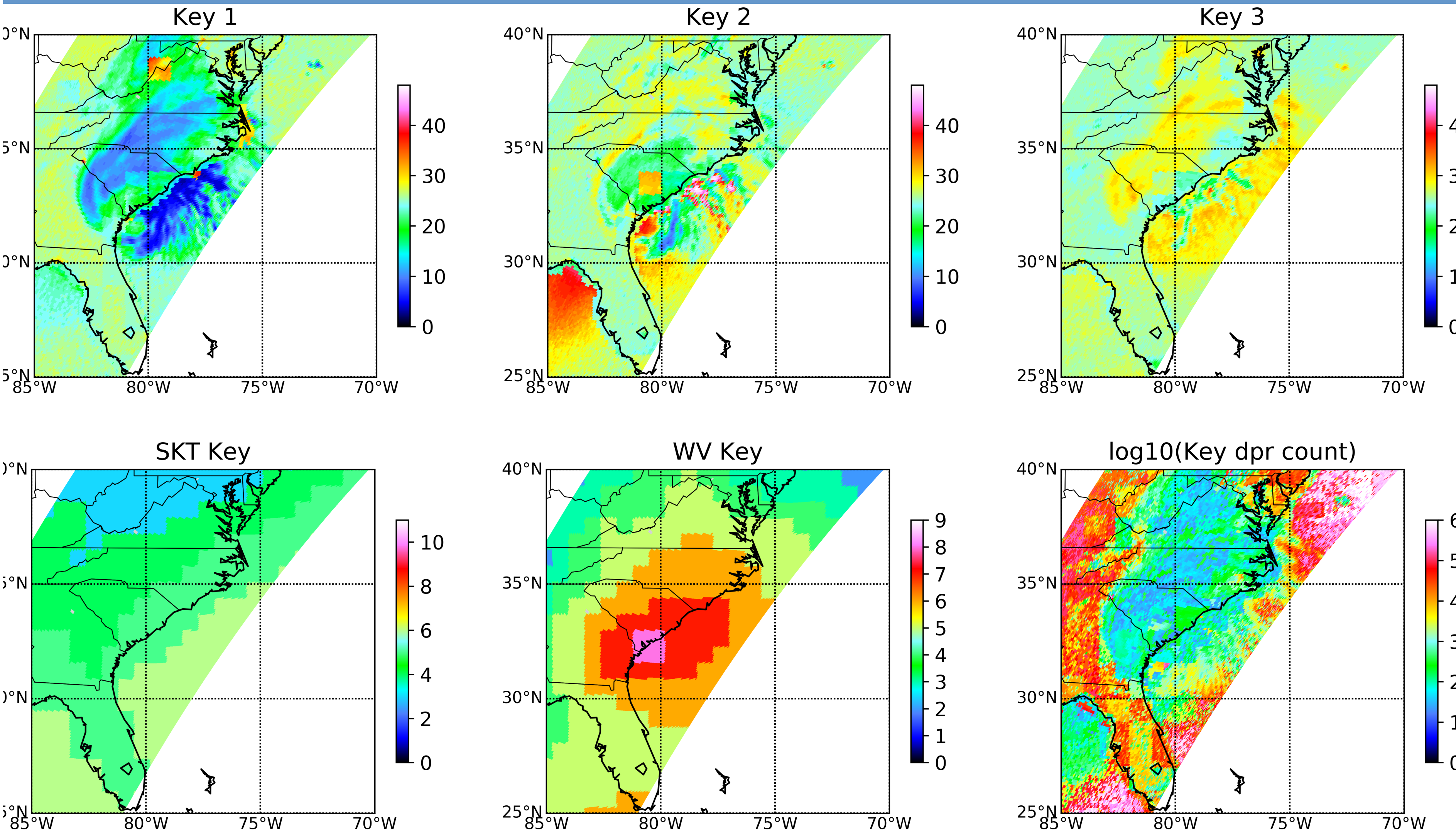

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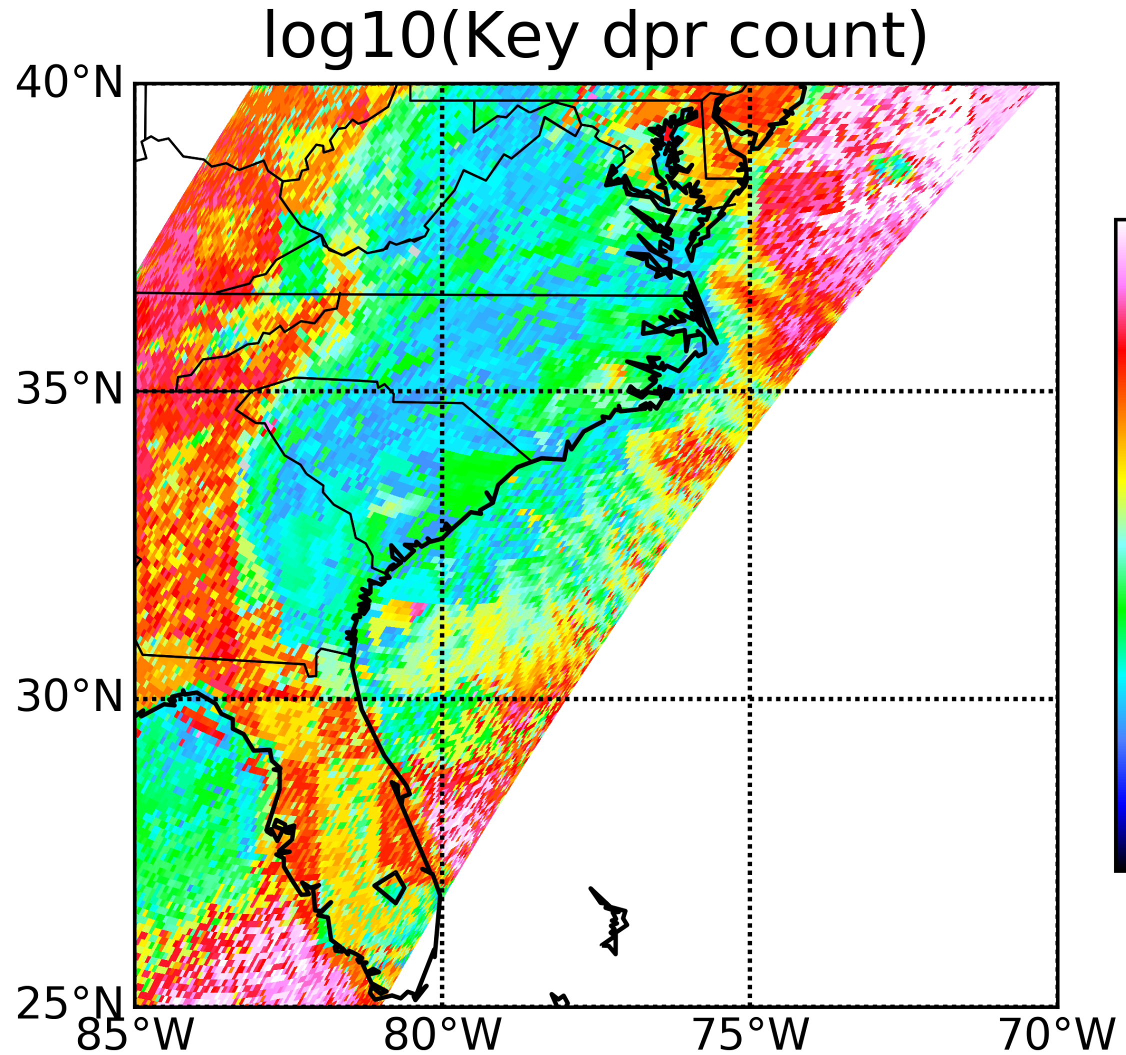

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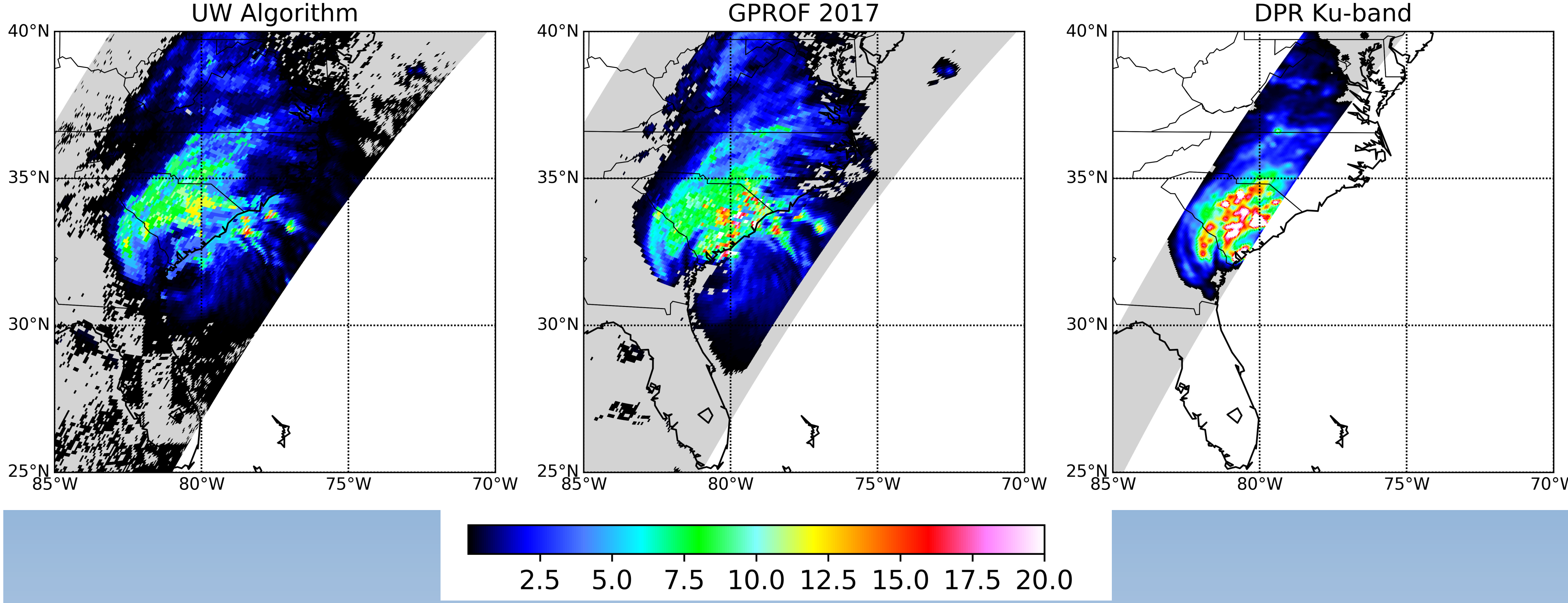

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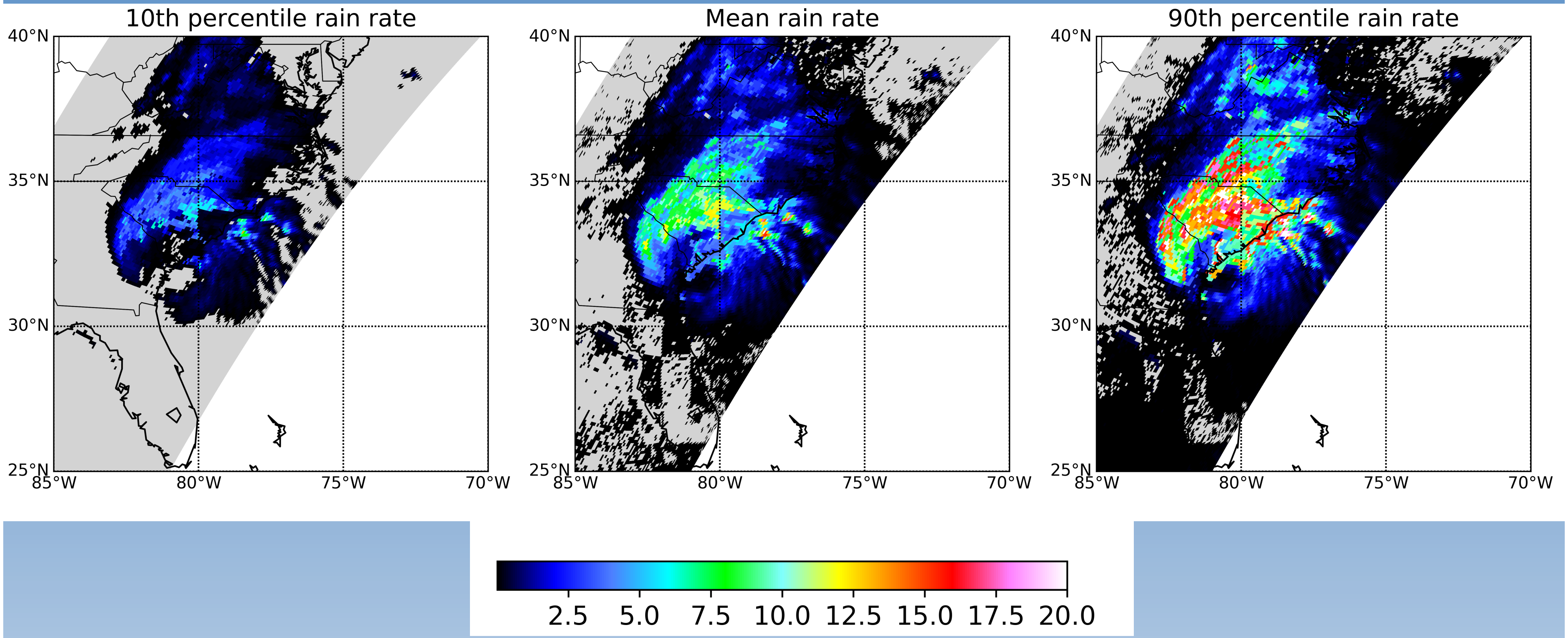
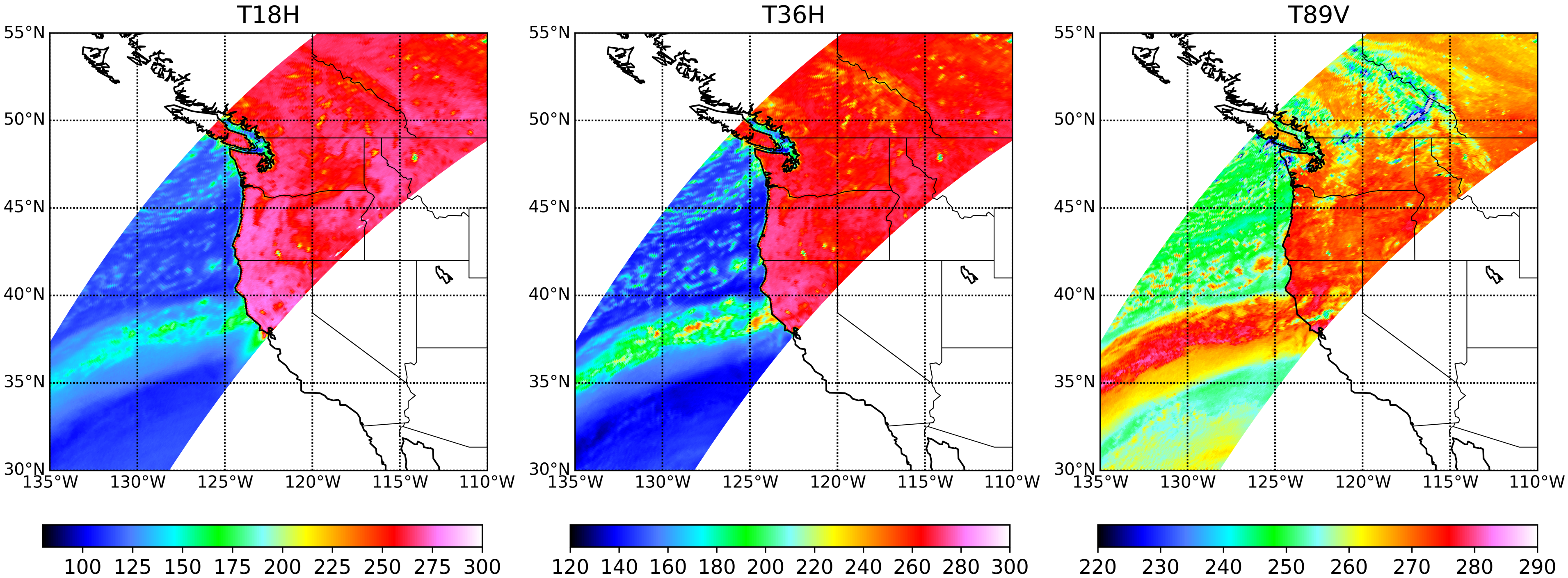
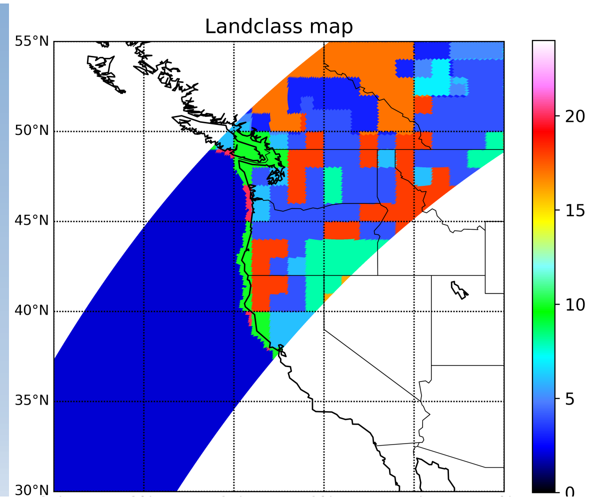
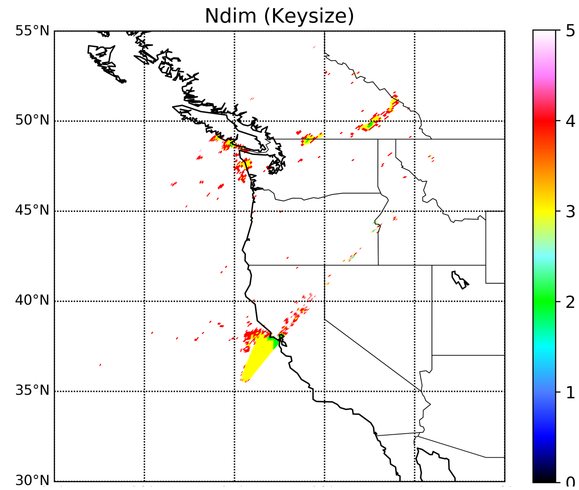


# Pacific Northwest

Nov. 1, 2015



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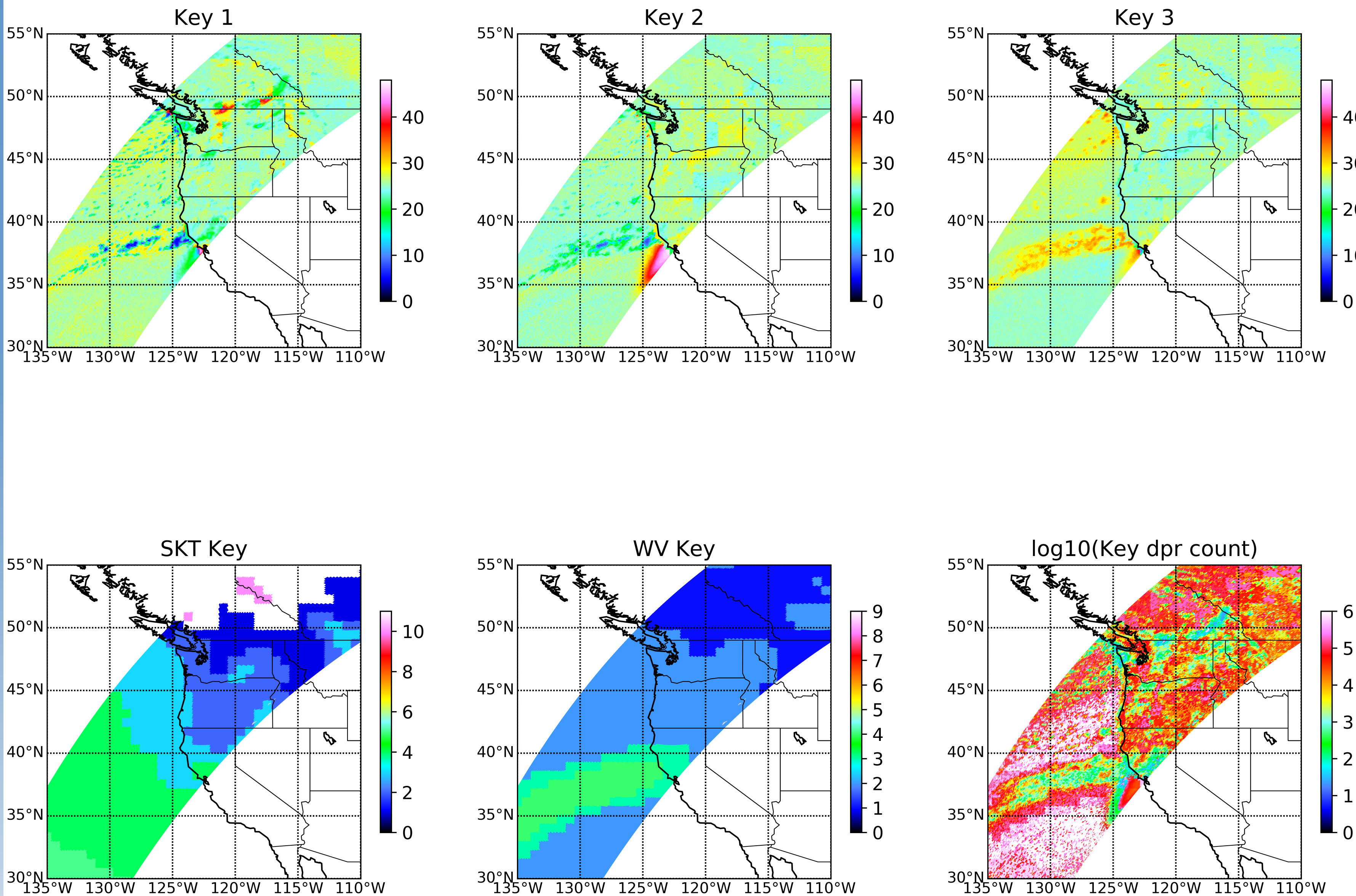

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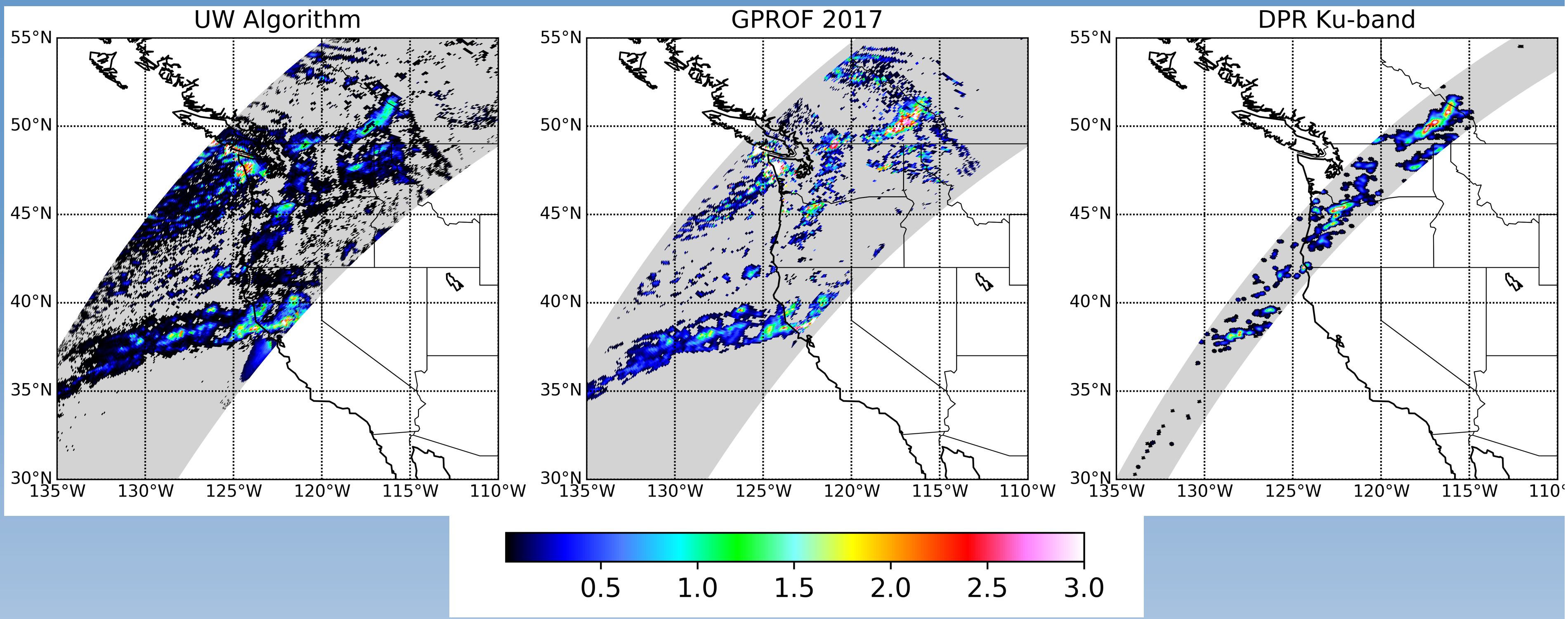

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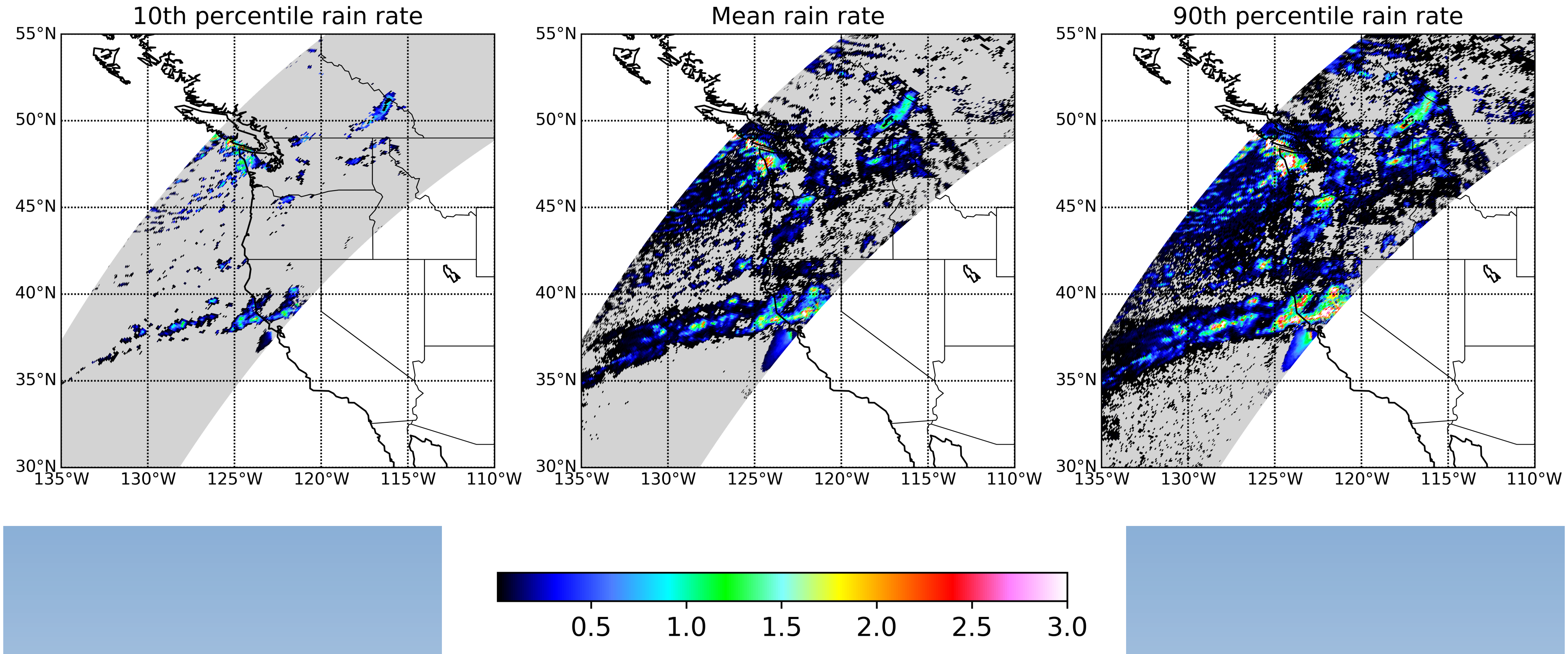
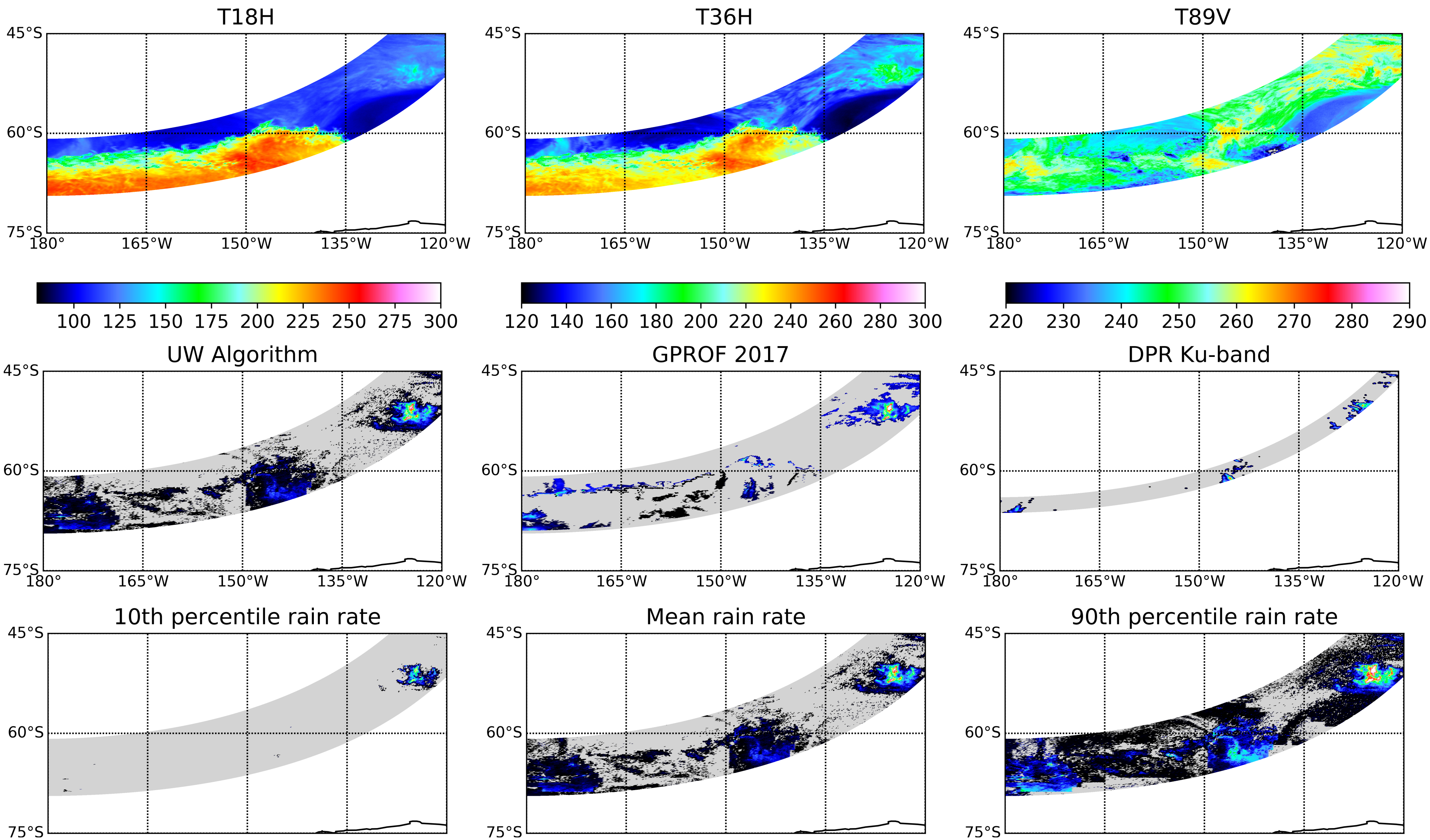


# Antarctic Marginal Ice Zone

October 8, 2016



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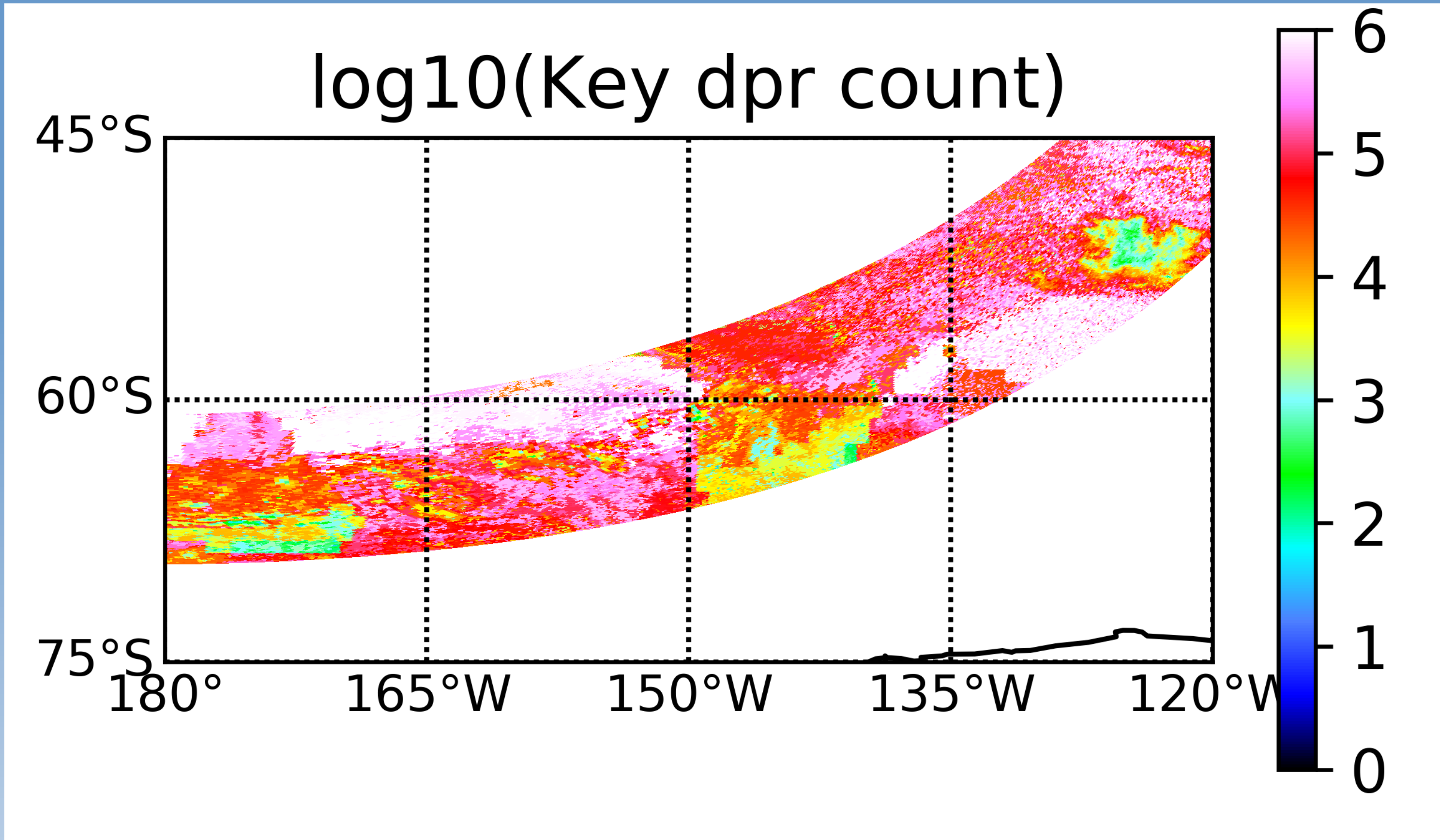

# Summary

- The UW-Madison algorithm has been successfully adapted to GMI and has been "trained" on over 340 million matchups between near-nadir DPR and resolution-matched GMI.
- Raw validation statistics are not necessarily meaningful without context – question is whether they *improve* on alternative methods when applied to identical scenes.
  - Intercomparisons needed.
  - Metrics should including examination of the "noise floor", not just traditional RMS error, bias, etc.
- The UW-algorithm is unique in providing not only estimates of the expected rain rate but also **posterior PDFs/CDfs/ quantiles of rain rate** associated with a given scene, as determined by the typically large set of qualifiying matches.

# Acknowledgments


- NASA PMM Grant #NNX16AF70G